Insights into Working Memory from The Perspective of The EPIC Architecture for Modeling Skilled Perceptual-Motor and Cognitive Human Performance*

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Abstract

Computational modeling of human perceptual-motor and cognitive performance based on a comprehensive detailed information-processing architecture leads to new insights about the components of working memory. To illustrate how such insights can be achieved, a precise production-system model that uses verbal working memory for performing a serial memory-span task through a strategic phonological loop has been constructed with the Executive-Process/Interactive-Control (EPIC) architecture of Kieras and Meyer. The model accounts well for empirical results from representative memory-span studies. The success of this account stems from five central features of EPIC that may be compared and contrasted with those of other currently popular alternative theoretical frameworks (Miyake & Shaw, in press). These features include: (1) formal implementation with multiple component mechanisms for perceptual, cognitive, and motor information processing; (2) representation of procedural knowledge in terms of a production system whose condition-action rules are all applied simultaneously and repeatedly during the cyclic operation of a central cognitive processor; (3) executive control procedures that schedule task activities efficiently and coordinate the use of limited-capacity peripheral perceptual-motor processors; (4) explicit simulations that yield accurate quantitative behavioral data; (5) relatively parsimonious implementation.

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Introduction

During the past several years, we have been developing a comprehensive theoretical framework for symbolic computational modeling of skilled perceptual-motor and cognitive human performance (Kieras & Meyer, 1994, 1995, 1997; Meyer & Kieras, 1992, 1994, 1997a, 1997b, 1998). A principal objective of our research is to formulate precise detailed computational models of performance in realistic multiple-task situations such as aircraft-cockpit operation, air-traffic control, and human-computer interaction. Through such modeling, it may be possible to improve the designs of person-machine interfaces, the selection of personnel, and the content of training programs that will facilitate performance significantly.

Because cumulative scientific progress requires "starting simple" and gradually dealing with more and more complex phenomena, our research has focused initially on the performance of relatively elementary tasks. For example, we have spent considerable effort on modeling performance under the psychological refractory-period (PRP) procedure, a basic dual-task paradigm that requires people to perform two discrete choice-reaction tasks concurrently. Some of our other related research has entailed modeling the concurrent performance of discrete choice-reaction and continuous visual-manual tracking tasks. In most (though not all) cases, the load imposed by these tasks on working memory has been light.[1] Thus, the components that mediate working memory in our theoretical framework have not required extensive elaboration yet. Nevertheless, it is clear that to thoroughly model the performance of complex tasks like aircraft-cockpit operation and air-traffic control, we must take the contributions and limitations of working memory more fully into account.

Such further treatment of working memory in the context of a practical computational-modeling project has much to recommend it. We have found previously that formulating computational models to account for substantial sets of empirical data can provide deep and surprising new insights about human information processing and major phenomena associated with it. On occasion, such insights may directly contradict prevailing theoretical beliefs; for example, the belief that there is an immutable structural response-selection bottleneck in the human information-processing system (Pashler, 1994; Welford, 1967) has been refuted by some of our discoveries. Similarly, it may be anticipated that formulating more precise computational models for various diverse mechanisms of working memory will yield additional insights.

Toward this end, we take "working memory" to encompass the entire ensemble of temporary stored codes, knowledge representations, and procedures whereby information is maintained, updated, and applied for performing perceptual-motor and cognitive tasks. Our current definition is consistent with the seminal use of "working memory" by Miller, Galanter, and Pribram (1960), who pioneered the theoretical discussion of this term. Our definition is also, by and large, consistent with those of other contributors to the present book (Miyake & Shaw, in press).

More specifically, this chapter considers working memory from the perspective of a particular architecture for characterizing the human information-processing system. Such architectures are essential to construct because they provide theoretical foundations and sets of mechanisms for human cognition and action, through which veridical computational models of performance can be formulated for specific tasks. In accord with the proposals made by Anderson (1976) and by Laird, Rosenbloom, and Newell (1986), the construction of information-processing architectures has become acknowledged as a fundamental theoretical approach for cognitive science and experimental psychology (Newell, 1990). This approach synthesizes multiple basic concepts, subsuming a variety of "micro" models and mechanisms into a single coherent whole. When an information-processing architecture is implemented computationally, its implications and

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[1] One important exception involves models that we have formulated to account for data collected by Ballas, Heitmeyer, and Perez (1992a, 1992b), who studied the concurrent performance of tactical-decision and visual-manual tracking tasks under conditions similar to those in aircraft operations, where an operator's global "situation awareness" plays a key role (cf. Graves, 1997; Gugerty, 1997).

applicability can be explored rigorously. The progress of serious cognitive theorizing requires the development of more comprehensive and accurate architectures, as exemplified by several contributions to this book (e.g., Lovett, Reder, & Lebiere; Schneider; Young & Lewis).

In what follows, the *Executive-Process/Interactive-Control* (EPIC) architecture that we have constructed for modeling cognition and action is described and applied to address issues about working memory. EPIC incorporates many recent theoretical and empirical results concerning human performance in the form of a simulation software system. Using EPIC, a computational model can be formulated to represent procedures for performing a complex multimodal task with an explicit set of production rules. When an EPIC model is supplied with external task stimuli, it executes the procedures in whatever way the task requires, thereby emulating a human who performs the task, and generating predicted actions in simulated real time.

EPIC is an architecture devoted explicitly to constructing models of skilled performance; it is not yet a learning system per se, and so at this time has a different scope than do the theoretical frameworks of some other contributors (e.g., Schneider; Young & Lewis) to this book. Instead, EPIC's current purpose is to characterize the perceptual and motor, as well as cognitive, constraints on people's ability to perform various tasks. Consistent with this purpose, the next section describes the components of the EPIC architecture. Then we introduce an instructive computational model based on EPIC to account for results from representative studies of verbal working memory.

The EPIC Architecture

Figure 1 outlines the overall organization of the component processors and memory stores in the EPIC architecture. At this level, EPIC resembles some previous theoretical frameworks for human information processing. Nevertheless, it constitutes a new synthesis of concepts and empirical results, being more comprehensive, detailed, and veridical than its predecessors.

We have designed EPIC to combine mechanisms for cognitive information processing and perceptual-motor activities with procedural task analyses of skilled performance. Our efforts complement production-system theories such as CCT (Bovair, Kieras, & Polson, 1990), ACT-R (Anderson, 1993; Lovett et al., this book), and Soar (Laird et al., 1986; Young & Lewis, this book). EPIC has a central cognitive processor surrounded by peripheral perceptual and motor processors. Applying EPIC to model the performance for a task requires specifying both the production-rule programming of the cognitive processor and the relevant operations of the perceptual and motor processors. When an EPIC model interacts with a simulated task environment, it produces an explicit sequence of overt serial and parallel actions required to perform the task, just as a human performer does. The procedural task analysis embodied in an EPIC model is general to a class of task scenarios (cf. John & Kieras, 1996).

The software for implementing EPIC is currently written in Common LISP. All EPIC models described in this chapter and elsewhere have actually been implemented and run to generate reported simulation results. EPIC really works! [2]

The EPIC framework includes not only software modules for simulating a human performer, but also provisions for simulating interactions of the performer with external equipment. For example, the left side of Figure 1 shows a simulated task environment, where virtual devices such as a display screen and keyboard provide the "physical" interface to a simulated performer on the right. During simulations with EPIC, the task-environment software module assigns physical locations to the interface objects, and it generates simulated visual and auditory events in response to the simulated performer's behavior.

[2] Our simulation software and a technical description of EPIC are available at ftp.eecs.umich.edu /people/kieras/EPICarch.ps.

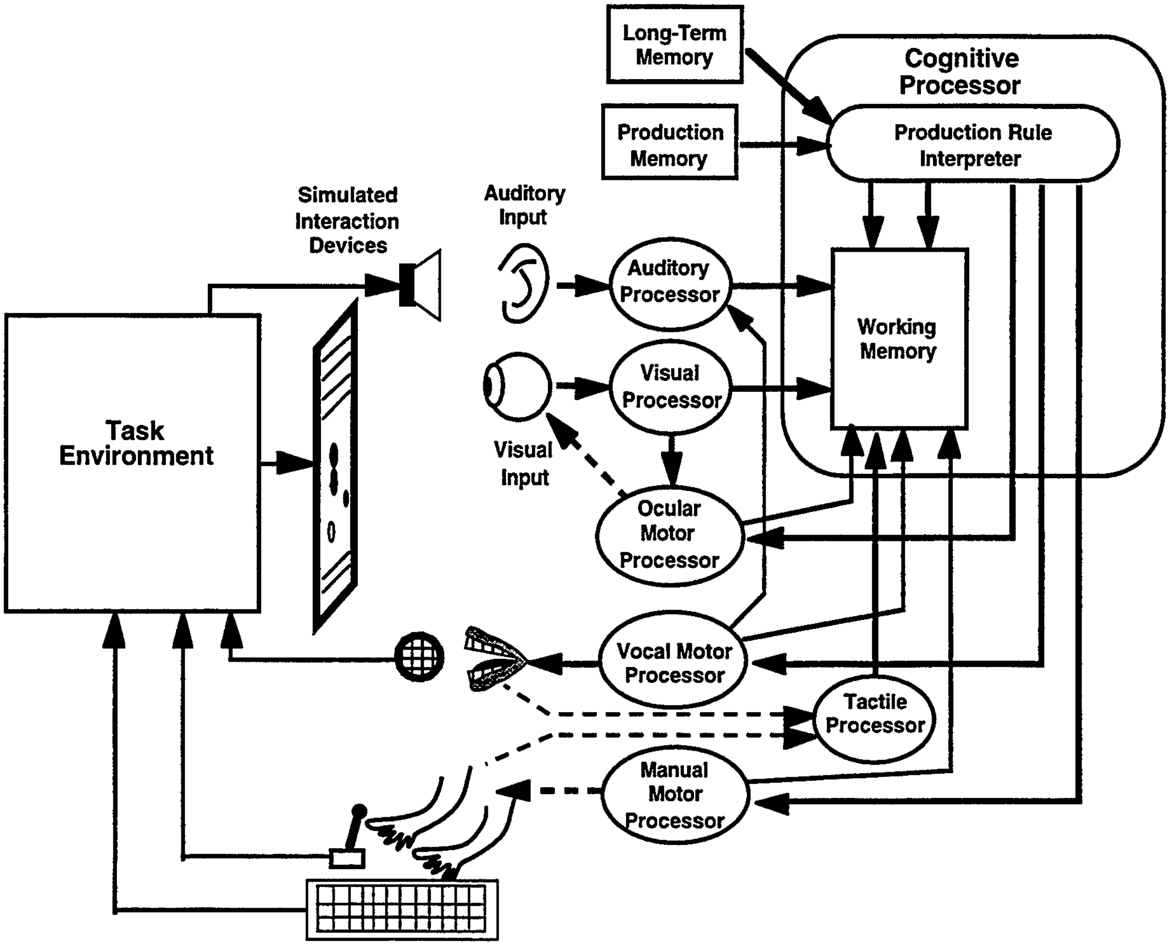

Figure 1. Overview of the EPIC architecture (adapted from Meyer & Kieras, 1997a).

Within the EPIC architecture (Figure 1), information flows forward from peripheral sensors, through perceptual processors, to a cognitive processor (with a production-rule interpreter and working memory), whose outputs control motor processors that move peripheral effectors. The architecture also has multiple feedback pathways. Its degree of perceptual-motor development is substantially greater than found previously in other popular information-processing architectures such as the Model Human Processor (Card, Moran, & Newell, 1983), ACT-R (Anderson, 1993; Lovett et al., this book) and Soar (Laird et al., 1986; Newell, 1990; Young & Lewis, this book).

EPIC has separate perceptual processors with distinct temporal properties for several major sensory (e.g., visual, auditory, and tactile) modalities. There are also separate motor processors for several major motor (e.g., ocular, manual, and vocal) modalities. Feedback pathways from the motor processors and effectors to partitions of working memory help coordinate multiple-task performance.

The declarative/procedural distinction made by "ACT-class" architectures (e.g., Anderson, 1976, 1993; Lovett et al., this book) is embodied in EPIC with separate permanent memory stores for procedural knowledge (production rules) and declarative knowledge (propositions). EPIC's working memory contains all of the temporary information needed for and manipulated by a model's production rules, including control items such as task goals and sequencing indices, along with representations of received sensory inputs and selected motor outputs. These various types of

information are stored in separate working-memory partitions such as auditory working memory, visual working memory, the control store, and the tag store.

Under EPIC, there are three different types of numerical parameter: *standard*, *typical*, and *free*. The numerical values of standard parameters (e.g., the mean cycle duration of the cognitive processor) stay the same across all applications of the architecture. The numerical values of typical parameters (e.g., the time required to detect a visual stimulus) are derived from prior results in the literature on human performance (e.g., Atkinson, Hernstein, Lindzey, & Luce, 1988; Boff, Kaufman, & Thomas, 1986); we set them on an *a priori* basis before simulations with an EPIC model are run, but they may change across different task contexts. The numerical values of free parameters also may change across different task contexts; they are estimated iteratively by determining which values maximize the goodness-of-fit between simulated and empirical data. We hope that through further modeling experience, more and more free parameters in EPIC will become standard or typical ones, thereby increasing our models' predictive power. Nevertheless, even now, the predictive power of our models is substantial.

Perceptual Processors

EPIC has perceptual processors for the visual, auditory, and tactile sensory modalities. They are simple "pipelines" through which information feeds forward asynchronously in parallel. Each stimulus input to a perceptual processor may yield multiple symbolic outputs that are deposited in working memory at different times. In addition, EPIC's tactile perceptual processor transmits feedback from effector organs to working memory. This can be important for coordinating performance of multiple tasks. Further details about EPIC's visual perceptual processor appear in Kieras and Meyer (1997). For now, we focus on the auditory perceptual processor, which is used extensively by the present EPIC computational model of verbal working memory.

***Auditory perceptual processor*.** The auditory perceptual processor receives inputs from EPIC's ear and sends outputs to auditory working memory, where representations of stimulus sounds are stored. For example, when the auditory perceptual processor receives a short tone signal, it may first produce a symbolic item that corresponds to the onset of the tone (standard delay: 50 ms), then at a later time, an item that identifies the frequency of the tone (typical delay: 250 ms), followed by an item that corresponds to the tone's offset (standard delay: 50 ms). Later, such items simply disappear from auditory working memory in an all-or-none manner after stochastic decay times whose magnitudes are consistent with typical durations of temporary stored auditory information (Balota & Duchek, 1986; Cowan, 1984; Cowan, Lichty, & Grove, 1990; Eriksen & Johnson, 1964; Watkins & Todres, 1980).

Following proposals by some previous investigators (e.g., Longoni, Richardson, & Aiello, 1993), the auditory perceptual processor codes external (overt) speech in the form of items for individual words and word sequences, which then go to auditory working memory just like coded information about tones does. We assume that specific amounts of time are required to identify individual words and to put their representations in working memory (typical delay: 150 ms). The auditory perceptual processor can also receive speech inputs from the vocal motor processor; such inputs whose source is internal (covert) have a distinct code that differentiates them from speech inputs whose source is external (overt).

***Representation of serial order*.** To represent the serial order of speech inputs, EPIC's auditory perceptual processor produces items that contain abstract symbolic tags pointing to the previous and to the next items of a sequence. Using these tags, a set of production rules can step through the stored items in auditory working memory for a series of spoken words, processing them one after another to complete a given task. Spoken items that come from external or internal sources are kept in separate source-specific sequential chains.

Of course, the format that we have chosen initially for representing the serial order of speech in EPIC is rather rudimentary and may require elaboration to explain or predict certain complex data. Nevertheless, there are precedents and virtues to recommend our chosen format (e.g., see Rumelhart & McClelland, 1986; Wicklegren, 1969). If and when the need arises, this format may be elaborated so that it accommodates hierarchical structures as well as sequential chaining (cf.

Anderson & Matessa, 1997; Estes, 1972; Healy, 1974; Gordon & Meyer, 1987; Henson, Norris, Page, & Baddeley, 1996; Lashley, 1951; Shiffrin & Cook, 1978).

Cognitive Processor

EPIC's cognitive processor is programmed in terms of production rules and it uses the Parsimonious Production System (PPS) interpreter (Bovair et al., 1990). PPS production rules have the format (<rule-name> IF <condition> THEN <actions>). The rule condition refers only to the contents of the production-system working memory. The rule actions can add or delete items in working memory, and also send commands to the motor processors.

Cyclic operation. The cognitive processor operates cyclically, consistent with known periodicities of the human information-processing system (Callaway & Yeager, 1960; Kristofferson, 1967; Ray, 1990). At the start of each cycle, the contents of working memory are updated with new outputs from the perceptual processors and the actions of applicable rules on the preceding cycle. At the end of each cycle, commands are sent to the motor processors.

The cognitive-processor cycles are not synchronized with external stimulus and response events. Inputs from the perceptual processors are accessed only intermittently, when the production-system working memory is updated at the start of each cycle. The cognitive processor typically has a cycle time that is stochastic with a mean of 50 ms (cf. Young & Lewis, this book; Newell, 1990). All other time parameters in the system are scaled proportionately with respect to the current randomly-sampled cycle time. The variance of the cycle-time distribution is chosen to produce an approximately 20% coefficient of variation for simple reaction times, corresponding to typical observed values.

Production-system parallelism. Most traditional production-system architectures let only one production rule be fired at a time, and only its actions are executed then (e.g., Anderson, 1976, 1993; Lovett & Reder, this book). Under these systems, when more than one rule has conditions that match the current contents of working memory, some kind of conflict-resolution mechanism must choose which rule to fire. Soar (Laird et al., 1986; Young & Lewis, this book) is perhaps the most complex case, in that its production rules only propose operators to apply, and many candidate operators can be proposed at once, but then a separate process must decide which particular candidate to apply.

In contrast, the Parsimonius Production System of EPIC's cognitive processor has a very simple policy: on each processing cycle, PPS fires all rules whose conditions match the current contents of working memory, and PPS executes all of their actions. Thus, EPIC models have true parallel cognitive processing at the production-rule level; multiple "threads" or processes can be represented with sets of rules such that they all run concurrently. Reaction-time data from basic multiple-task performance, which demonstrate the absence of a central cognitive response-selection bottleneck, strongly support our assumptions about the cognitive processor (Meyer et al., 1995; Schumacher et al., 1997, 1998).

Our theoretical approach with respect to the nature of information-processing limitations is also a matter of scientific tactics: we make some radically simple assumptions and then explore their consequences. EPIC starts with obvious inherent limitations of human memory and perceptual-motor mechanisms; it incorporates other more elaborate and debatable constraints only when serious failures at accounting for empirical data compel us to do so. In part, such extreme parsimony differentiates us from other contributors to this book (cf. Lovett et al.; O'Reilly, Braver, & Cohen; Schneider; Young & Lewis). Perhaps because it foregoes elaborate incorrect assumptions, our approach has fared reasonably well thus far.

Working memory

As mentioned already, the working memory for EPIC's cognitive processor does, of necessity, have several partitions. Taken together, their contents provide EPIC computational models with a basis for maintaining overall situation awareness under both laboratory conditions and real-world circumstances where "cognition in the wild" occurs (e.g., Graves, 1997; Gugerty, 1997; cf. Engle et al., this book).

Modal working-memory stores. Three partitions of working memory are dedicated to specific perceptual modalities. These include visual, auditory, and tactile stores that contain information from the respective perceptual processors. Items persist there in an all-or-none manner for durations that depend on the types of information involved. EPIC also has a motor working memory that contains information about the current states of the motor processors.

Production-system memory stores. Two other partitions of working memory are production-system memory stores. These include a control store and tag store. They contain information defined only in terms of the contents of production rules. By using them together with EPIC's modal working-memory stores, motor processors, and perceptual processors, the cognitive processor may implement other working-memory mechanisms such as a phonological loop (cf. Baddeley, 1986; Baddeley & Logie, this book).

Control store. In the control store are items that represent current task goals and procedural steps for accomplishing them. Under PPS, such items are treated just like other types of information in working memory, and so they can be freely manipulated by rule actions. This is crucial for modeling multiple-task performance, because it enables the production rules of an executive process to coordinate the progress of task subprocesses.

The control store contains several types of item: (1) *goals*, which appear in the conditions of rules that accomplish a particular task; (2) *steps*, which cause rules to fire in a specific sequence; (3) *strategy items*, which enable or disable rules for implementing alternative versions of a task strategy; (4) *status items*, which represent the current states of various subprocesses, such as indicating what ones are now under way. Items in the control store have meaning only with respect to the production rules that test for, add, or delete them; they are not related by an "external semantics" to overt perceptual or motor events.

For now, the control store is assumed to have unlimited capacity and duration (cf. Lovett et al., this book). Thus, in practice, the number of items that it contains at any moment depends only on which task processes are being executed. The executive and task processes of our models typically delete control-store items whenever they are no longer needed. We await future theoretical and empirical results to determine whether the control store should have more constrained limits.

Tag store. The tag store contains items that "label" other items in the modal (i.e., perceptual and motor) working memories. Such labeling assigns particular roles to modal working-memory items referenced by the conditions and actions of production rules. For example, a production rule might update the tag store with a new tag for an object in visual working memory, labeling it as "the stimulus". This would specify which object is "the stimulus" to be checked subsequently when the conditions of other rules are tested for their truth-values.

Under EPIC, each item in the tag store refers to only one item in a modal working-memory store. The contents of a tag include only internal symbols; like control-store items, tags have no "external semantics". As for the control store, we likewise assume that the capacity and duration of the tag store are unlimited, and that executive or task processes delete tag items when they are no longer needed. Again we await future theoretical and empirical results to determine whether the tag store should have more constrained limits.

Illustrative production rule. The following production rule illustrates some of EPIC's different possible working-memory items and production-rule actions:

```
(EXAMPLE-RULE:
   IF
   ((GOAL DESIGNATE TARGET
     (STRATEGY MAKE POKE IMMEDIATELY)
     (STEP  MAKE POKE-RESPONSE)
     (TAG ?OBJECT IS STIMULUS)
     (VISUAL ?OBJECT COLOR RED)
     (NOT (VISUAL ??? SIZE LARGE))
     (STATUS PERF-TACTICAL RESPONSE-PROCESS HAS EYE)
     (MOTOR MANUAL PROCESSOR FREE))
   THEN
   ((SEND-TO-MOTOR MANUAL PERFORM POKE (LEFT INDEX) ?OBJECT)
     (ADDDB (GOAL WATCH-FOR DESIGNATION-EFFECT))
     (DELDB (STEP  MAKE POKE-RESPONSE))
     (ADDDB (STEP WAIT-FOR WATCHING-DONE))))
```

The function of this rule is to touch a small red object on a display screen, designating it as a target by poking it with the left index finger. Embedded in the rule's condition are multiple expressions that must be true conjunctively with respect to the contents of working memory: here the goal (control-store item) is to designate a target; the strategy (control-store item) is to make the poke movement immediately; the current procedural step (control-store item) calls for making a poke movement; a certain visual object has been tagged as "the stimulus" (tag-store item); the tagged stimulus object (visual working-memory item) is red; no large object is in view (i.e., visual working memory lacks any items about "large" objects); the process responsible for making the poke has a status (control-store item) that enables it to move EPIC's eye; and the state of the manual motor processor (control-store item) indicates that it is free to accept movement commands. If and when EPIC's various working-memory partitions contain all requisite items for matching this rule's condition, then one of the rule's actions will command the manual motor processor to make a poke movement with the left index finger at the stimulus object. Also, the rule's other actions will establish a new subgoal (control-store item) to be accomplished next, delete the current step item, and add an item for the next step.

Motor Processors

EPIC has separate motor processors for moving the hands, eyes, and speech articulators. All of them operate simultaneously. To operate a motor processor, the cognitive processor sends it a command that contains the symbolic name for a desired type of movement and its relevant parameters. Then the motor processor produces a simulated overt movement of its effector, achieving the specified temporal and spatial characteristics for this movement. Many further details about movement representation, preparation, and execution by EPIC's ocular and manual motor processors appear in Kieras and Meyer (1997). For now, we focus on the vocal motor processor, because it is especially relevant to the present EPIC model of verbal working memory.

Vocal motor processor. EPIC's vocal motor processor can produce either overt or covert spoken words, based on commands from the cognitive processor, which provides symbolic information about the desired utterance's style and content. Each spoken word is then sent as an input to the auditory perceptual processor (Figure 1). For overt speech, we assume that sound production is delayed by about 100 ms after articulatory initiation, and continues for an amount of time that depends on the number of syllables in each spoken word, as well as other relevant vocal parameters. Overt and covert speech are assumed to be produced motorically at essentially the same rate, consistent with empirical data (Landauer, 1962). During vocalization, an additional style parameter may specify intonation, acoustically marking each component word of a sequence as starting, continuing, or ending the sequence. A judicious combination of the vocal motor processor, auditory perceptual processor, and certain forms of working memory, operated through appropriate production-rule programming, may be used to construct EPIC models that have a plausible and precisely specified phonological-loop mechanism (cf. Baddeley & Logie, this book).

An EPIC Computational Model for Verbal Working Memory

The remainder of this chapter illustrates how EPIC can be applied for understanding and modeling human performance of tasks that involve intensive use of verbal working memory. For now, we focus on one prototypical case, the serial memory-span task (Miller, 1956). In what follows, an EPIC computational model is presented to account quantitatively for representative data from this task and to reach new insights about how working memory works.

Our present EPIC model incorporates a phonological-loop mechanism that, in some but not all respects, resembles ones proposed by previous theorists (e.g., Atkinson & Shiffrin, 1968; Baddeley & Hitch, 1974; Baddeley & Logie, this book; Schweickert & Boruff, 1986; Sperling, 1967; Waugh & Norman, 1965).[3] For the sake of veracity and parsimony, the phonological loop in EPIC is not a distinct new architectural component. Instead, it is implemented with EPIC's pre-existing auditory working memory and vocal motor processor, which had been incorporated previously to model other types of real-time performance. To implement a phonological loop, EPIC's vocal motor processor subvocalizes to-be-remembered items sequentially, relying on the chained representation format described earlier. The products of this subvocalization are traces in auditory working memory that disappear after a time, but that meanwhile can be used to vocalize the items again either covertly during further rehearsal, or overtly during final recall.

The total capacity of EPIC's phonological loop depends on the durations of items in auditory working memory and on the rate of subvocalization achieved with the vocal motor processor. This dependence is plausible because it stems from obviously required architectural constraints on human information processing. Consistent with our "minimalist" theoretical approach to architecture specification, we forego making additional gratuitous strong *a priori* assumptions about prevailing capacity limitations on working memory. Specifically, at present there is no assumed upper bound on the number of items that EPIC's auditory working memory may contain simultaneously. Nor does EPIC -- unlike alternative theoretical frameworks -- assume the existence of limited-capacity graded activation for items in its working-memory stores (cf. Anderson & Matessa, 1997; Just, Carpenter, & Hemphill, 1994; also, in this book, see Engle et al.; Lovett et al.; O'Reilly et al.; Schneider).

Serial Memory-Span Task

To facilitate the present theoretical endeavor, the version of the serial memory-span task on which we focus now involves discrete trials with a generic experimental design. This design has been a popular one (e.g., see Baddeley, Thomson, & Buchanan, 1975; Longoni et al., 1993; Standing, Bond, Smith, & Isley, 1980), and it typifies the studies whose empirical results are fit here with our EPIC model of verbal working memory. On each trial of these studies, a sequence of several (e.g., more than one but less than ten) words was presented auditorily at a constant moderate rate. After the last word of the sequence, which typically contained somewhere in the range of three to eight words, there was a recall signal, and a participant attempted to recall the presented words in their original order. Ample time (e.g., 15 s) was allowed for recall. Then a new trial began. For each trial, the presented words were drawn randomly from a small pool whose individual members got used repeatedly across trials but at most only once within a trial.[4]

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[3] We call the loop "phonological" to be consistent with terminology used by other authors (e.g., Baddeley & Logie) in this book. However, our use of this term is not meant to imply that the items in the loop have abstract phonological representations as defined by formal linguists (e.g., Akmajian, Demers, & Harnish, 1979). For present purposes, the items' representations may be more aptly called "auditory" and "articulatory". Thus, the mechanism described here may also be called an "articulatory loop", a term used frequently by past researchers (e.g., Baddeley et al., 1984; Burgess & Hitch, 1992; Gupta & MacWhinney, 1995). It remains an open question whether the items in the human articulatory loop have abstract "phonological" representations.

[4] This procedure for constructing the word sequences helps ensure that the task is performed simply on the basis of

The participant's attempted recall on a trial was scored as being correct if and only if all of the presented words were recalled in their original order. The dependent variable was the percentage of trials on which correct recall occurred.

Under conditions similar or identical to these, it has been found that several independent variables affect percent correct recall systematically. The observed effects include the following:

Sequence-length effect. Longer word sequences (i.e., ones that contain more words) are less likely to be recalled correctly than are shorter sequences (e.g., Baddeley et al., 1975).

Articulation-time effect. Sequences that take more time to articulate are less likely to be recalled correctly than are sequences that take less time to articulate (e.g., Baddeley et al., 1975; Cowan et al., 1992; Gupta & MacWhinney, 1995; Longoni et al., 1993; Schweickert, Guentert, & Hersberger, 1990).

Phonological-similarity effect. Sequences of phonologically similar words are less likely to be recalled correctly than are sequences of dissimilar words (e.g., Conrad & Hull, 1964; Longoni et al., 1993; Schweickert et al., 1990).

Articulatory-suppression effect. Recall is less likely to be correct when participants perform a concurrent secondary task that precludes subvocal rehearsal than when they do not (e.g., Baddeley, Lewis, & Vallar, 1984; Levy, 1971; Longoni et al., 1993).

Our present EPIC model accounts quantitatively for such effects, using parsimonius plausible assumptions. In so doing, it yields instructive insights about the true properties of human auditory working memory, vocal motor processing, and the phonological loop. Insights about possible cognitive control strategies for performing the serial memory-span task are also provided.

Architectural Implementation of EPIC Model

Implementing our present EPIC model required relatively minor extensions to a previous version of the architecture (Kieras & Meyer, 1997). For this implementation, we gave EPIC's vocal motor processor a new subvocalization style with prosodic markers. Furthermore, a new motor-perceptual connection was introduced so that covert speech outputs could be sent from the vocal motor processor to the auditory perceptual processor, which recognized them and put their symbolic representations in auditory working memory. The auditory perceptual processor was also elaborated somewhat. As a result, it produced distinct codes for speech that came from internal and external sources, creating separate sequential chains of spoken items, depending on what the source was. This instantiation of source-specific coding in auditory working memory is consistent with empirical results from some prior behavioral (Cowan, 1984) and brain-imaging (e.g., Awh et al., 1996; Paulesu, Frith, & Frackowiak, 1993) studies.

Regarding auditory working memory, we also made six more assumptions: (1) No limit exists on the number of items stored there. (2) The loss or "decay" of a stored item is an all-or-none process. (3) Individual stored items have stochastically independent decay times. (4) Decay time has a lognormal distribution with two parameters, M, the median of the distribution, and s, the "spread" of the distribution.[5] (5) The values of M and s are affected by the stored items' phonological similarity and the type of source (external or internal) from which they come. (6) Information about serial order is contained in the stored items as supplementary tags that form an implicit "linked list" chain structure.

Several virtues of these assumptions should be mentioned. Although seemingly elaborate, they are essentially minimal ones required to account accurately for data from the serial memory-

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phonological-loop mechanisms rather than graded levels of activation in long-term memory, as some other theorists (e.g., Anderson & Matessa, 1997; Lovett et al., this book) have assumed.

[5] The lognormal distribution is unimodal and positively skewed over the non-negative real numbers (Hastings & Peacock, 1975). These features are presumably ones that distributions of real decay times have. Parameterization with M and s facilitates implementing and interpreting effects caused by changes in the lognormal distribution's central tendency and dispersion.

span task. Results of past studies support some of them. Evidence for spontaneous decay of stored items in working memory has been reported (e.g., J. Reitman, 1974; cf. Shiffrin, 1973), consistent with Assumption 2. The probability of item decay increases as time passes (Brown, 1958), consistent with Assumption 4. Phonological similarity of stored items can shorten their decay times (Posner & Konick, 1966), consistent with Assumption 5. Linked-list chain structures may mediate vocal item-successor naming (Sternberg, 1969) and word-sequence production (Sternberg et al., 1978), consistent with Assumption 6.

Furthermore, the task strategy that our EPIC computational model uses to control its phonological loop for performing the serial memory-span task can be justified on both theoretical and empirical grounds.

Strategy for The Serial Memory-Span Task

As mentioned already, modeling the performance of any task with EPIC involves specifying a task strategy and representing it in terms of production rules. From formulating such specifications, we have found that the strategies needed for using a phonological loop to perform verbal memory tasks are suprisingly subtle and complex. This is because these tasks require the processing of new stimulus inputs to overlap temporally, in a coordinated fashion, with on-going subvocal maintenance rehearsal of previously stored items.

For example, in performing the serial memory-span task, each cycle of rehearsal presumably yields a fresh copy of an item chain, with recently received items being appended to an immediately prior chain of older items. Thus, the task strategy must juggle multiple individual items and multiple chains of items simultaneously in auditory working memory. Although EPIC's auditory perceptual processor can extend an item chain automatically as successive new inputs arrive, the task strategy still has to keep track of "where" its component processes are currently working in various parts of different subchains. The situation is further complicated by the fact that as time passes, items can disappear haphazardly from auditory working memory and task strategies must deal with the problem of lost items. Figure 2 shows how this complexity may be managed under at least some circumstances.

Overall task strategy. The overall task strategy of our EPIC computational model for performing the serial memory-span task is outlined in Figure 2. Here we assume that after a trial starts, several concurrent processes with complementary functions are executed. Together, using the aforementioned representational formats of EPIC's auditory perceptual processor, vocal motor processor, and auditory working memory, these processes orchestrate the construction, rehearsal, and recall of item chains built from items whose source is either external (overt auditory stimuli) or internal (covert subvocal rehearsal). Given that EPIC has inherent multiprocessing capabilities, each such process constitutes a *thread* of execution, running independently and simultaneously with other processes during the trial.

Item-chain construction processes. One of the assumed item-chain construction processes (upper left part of Figure 2) keeps track of an *add-chain* that contains new items received from the external stimulus source. This involves waiting for each successive external stimulus item to arrive in auditory working memory and then tagging it as a "new" item for the add-chain. Another item-chain construction process (upper right part of Figure 2) keeps track of a *rehearsal chain* that contains covert speech inputs produced by on-going subvocal rehearsal. This involves waiting for each successive covert input and tagging it as a "new" item to be included in the next cycle of rehearsal. The most recent copy of the rehearsal chain and the current contents of the add-chain then get used during the next rehearsal cycle.

Rehearsal process. Under our present EPIC model, a cycle of rehearsal commences whenever either the first external stimulus item arrives in auditory working memory at the start of a trial, or an immediately preceding rehearsal cycle has been completed and the current add-chain contains some further external stimulus items that have not been rehearsed yet (see middle right part of Figure 2). If so, then the rehearsal process is assumed to go through the steps shown in Figure 3.

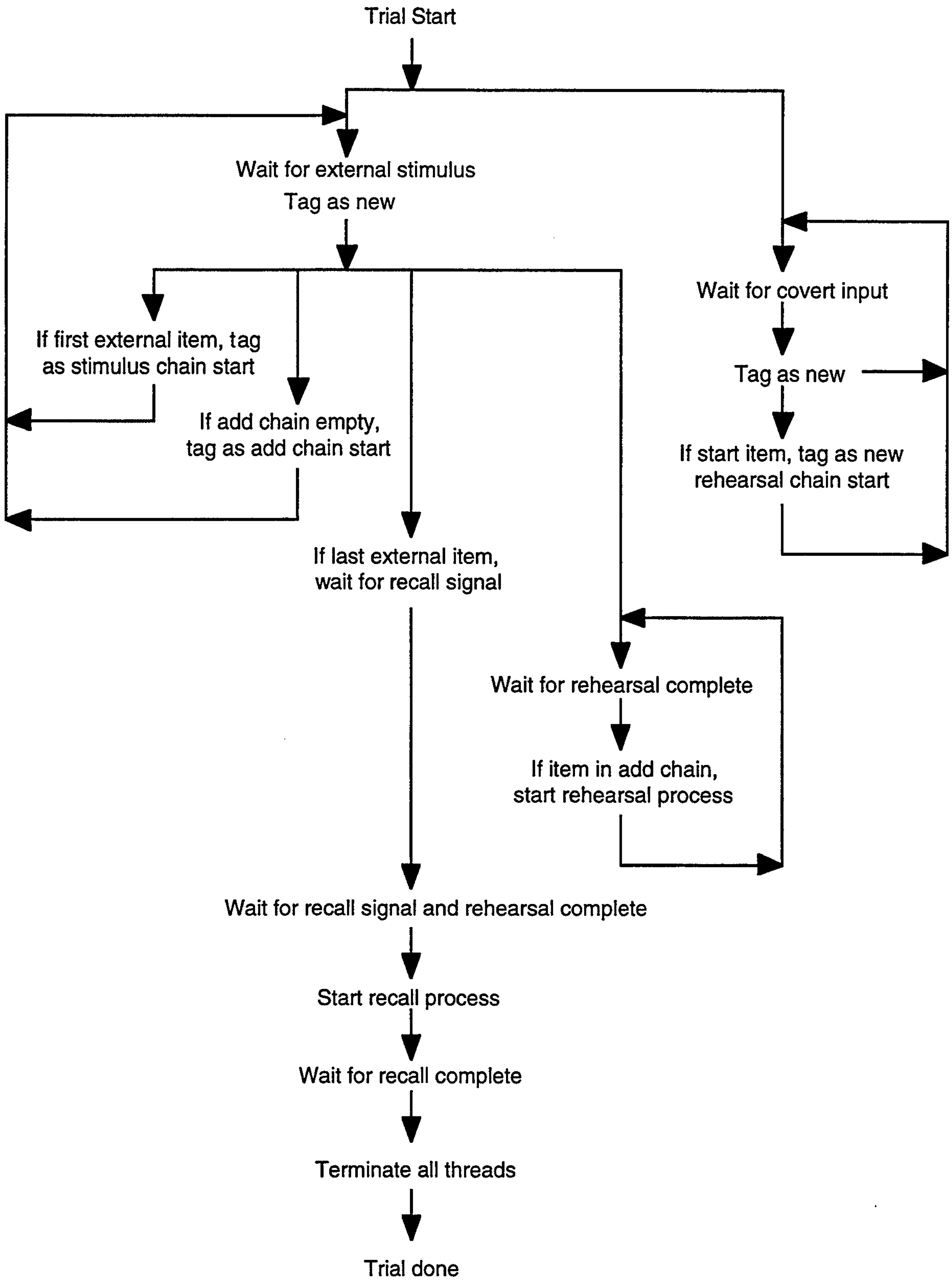


Figure 2. Flowchart of the overall task strategy used by the present EPIC model of verbal working memory for performing the serial memory-span task.

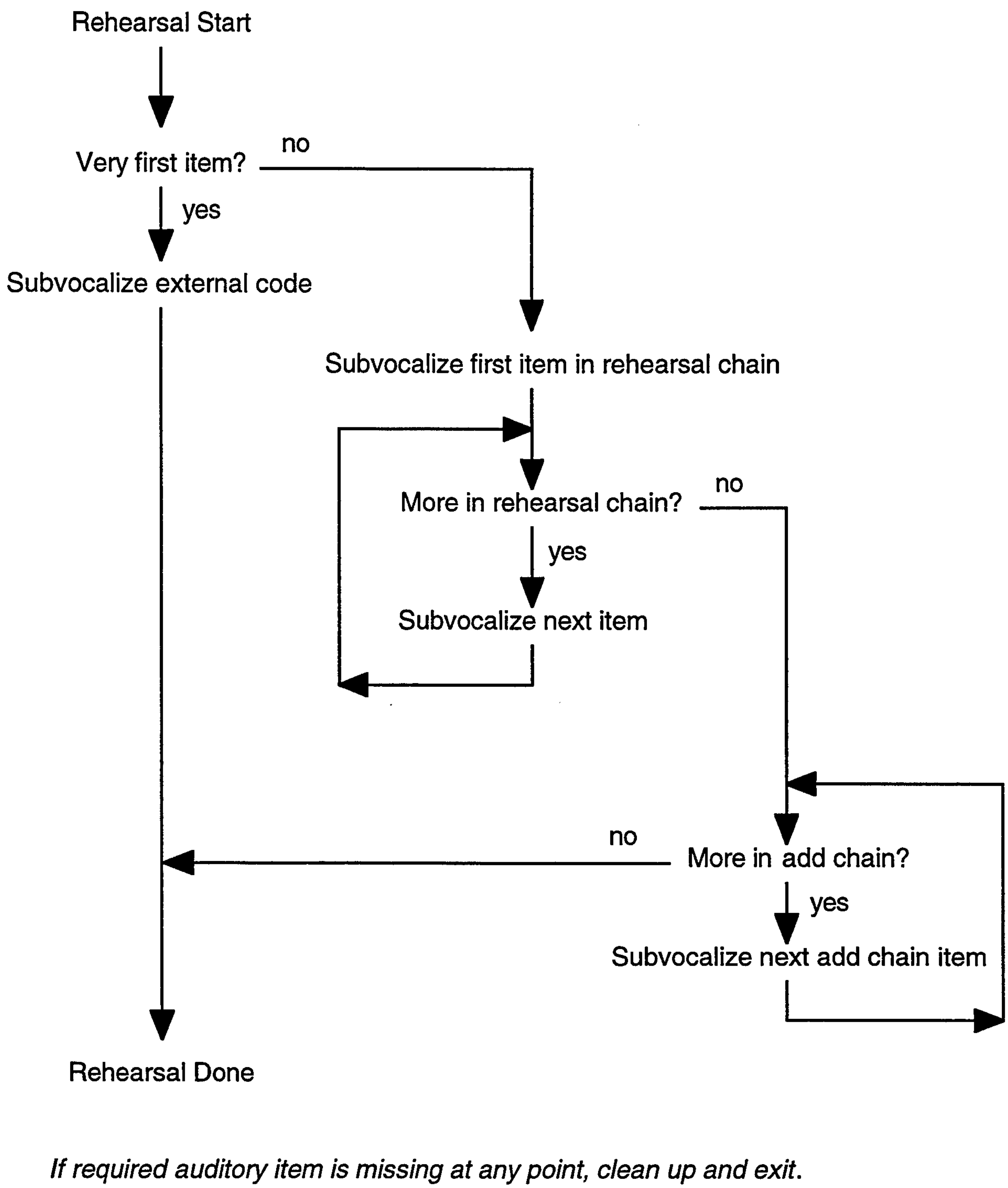


Figure 3. Steps in one cycle of the rehearsal process used by the present EPIC model of verbal working memory for performing the serial memory-span task (cf. Figure 2). A rehearsal cycle includes consecutive phases that, when need be, subvocalize the first external stimulus item on a trial, subvocalize each item of the current rehearsal chain in auditory working memory, and then subvocalize each item of the current add-chain.

During a cycle of rehearsal, there are three consecutive phases. First, the rehearsal process checks whether an initial external stimulus item has arrived in auditory working memory. If so, then it is sent by the cognitive processor to the vocal motor processor, which subvocalizes the item and transmits its covert output to the auditory perceptual processor for recoding and storage in auditory working memory. Otherwise, each internal item in the most recent copy of the rehearsal chain is sent successively to the vocal motor processor and subvocalized once, with the resulting covert outputs again going to the auditory perceptual processor and auditory working memory for recoding and storage, respectively. Next, any external stimulus items in the current add-chain are sent successively to the vocal motor processor and subvocalized so that internal-item (covert speech) representations of them can be appended to an updated copy of the rehearsal chain.

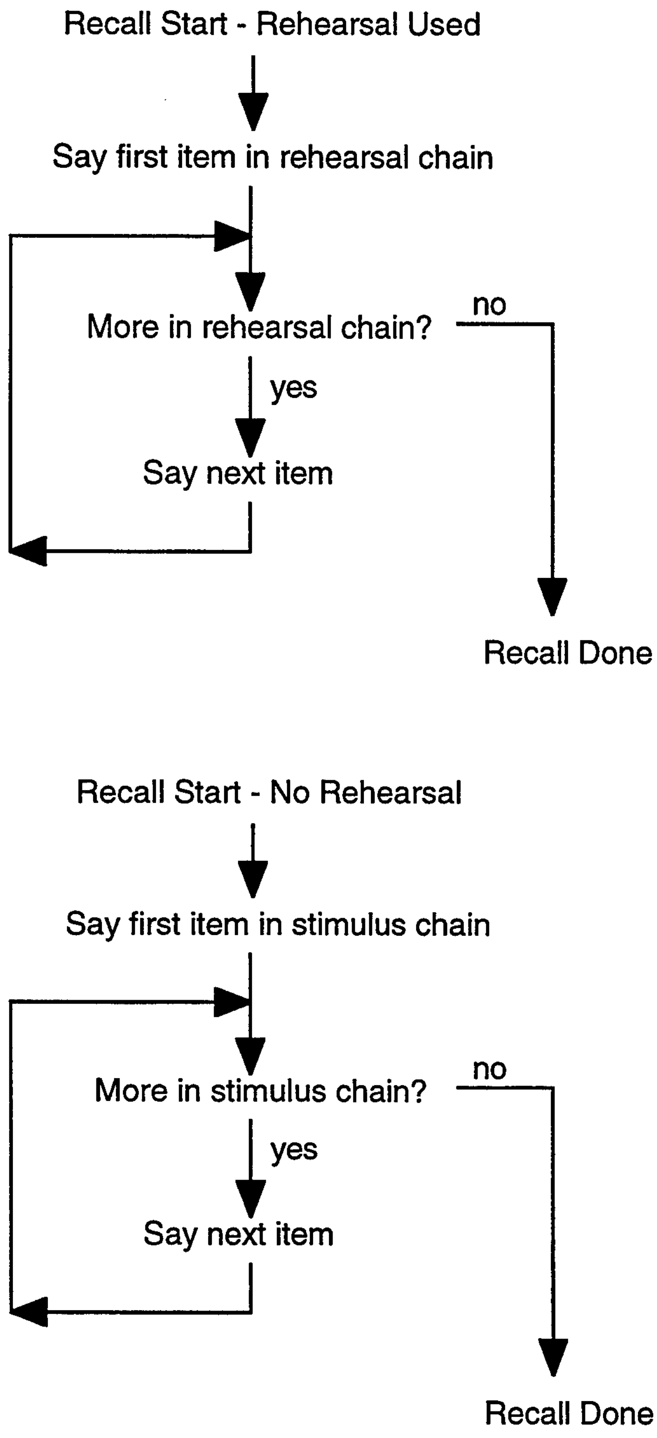
Serial-order tags associated with the individual items of these chains are used by the cognitive processor to govern their order of subvocalization. A rehearsal cycle terminates when neither the current rehearsal chain nor the add-chain contains any more items to be subvocalized at the moment. For the next cycle of rehearsal, the aforementioned item-chain construction processes specify the new rehearsal chain in auditory working memory, tagging its starting item as "new" so that the cognitive processor can access it appropriately. Individual items and item chains that have been used during previous rehearsal cycles are tagged as "old" but remain in auditory working memory, disappearing haphazardly from there as time passes.

A major complexity caused by haphazard item decay is that the rehearsal process may fail occasionally and unpredictably. Such failures can occur at any moment during a rehearsal cycle if an item in the current rehearsal chain or add-chain happens to disappear from auditory working memory before it has been subvocalized. As a result, rehearsal would be disrupted. Recovery and graceful continuation after these disruptions requires intervention by appropriate executive control procedures of the task strategy.

Recall processes. Successful performance of the serial memory-span task also requires a set of final recall processes. We assume that recall starts after the last external stimulus item has been received, a recall signal has been detected, and any rehearsal cycle in progress has been completed (see bottom middle part of Figure 2). What happens thereafter involves one or the other of two recall processes shown respectively in the top and bottom panels of Figure 4, which enter the picture when either rehearsal has occurred previously during the trial or it has not. The latter option must be accommodated along with the former because on some trials, concurrent articulatory suppression or other ancillary distractions may preclude subvocal rehearsal.

When rehearsal has occurred previously during the trial, the recall process attempts to vocalize every item in the most recent copy of the rehearsal chain (Figure 4, top panel). This vocalization proceeds by having the cognitive processor send the successive rehearsal-chain items one-by-one from auditory working memory to the vocal motor processor for overt output. As result, correct recall will occur if, and only if, all of the originally presented items were incorporated into the most recent rehearsal chain and remain there (i.e., do not decay) throughout the recall process.

When no rehearsal has occurred previously during the trial, the recall process instead attempts to vocalize the stored chain of external-stimulus items that were input originally by the auditory perceptual processor to auditory working memory (Figure 4, bottom panel). This vocalization proceeds by having the cognitive processor send the successive stimulus-chain items one-by-one from auditory working memory to the vocal motor processor for overt output. As above, correct recall will occur if, and only if, all of these items are still present in auditory working memory and remain there (i.e., do not decay) throughout the recall process. Because items in the original stimulus chain have had more time to decay than do items in the most recent copy of a rehearsal chain, articulatory suppression or other factors that preclude subvocal rehearsal and thereby force use of the original stimulus chain may decrease the frequency of correct recall.



If required auditory item is missing at any point, clean up and exit.

Figure 4. Recall process used by present EPIC model of verbal working memory for performing the serial memory-span task (cf. Figure 2). Top panel shows steps in recall after prior rehearsal has occurred on a trial. Bottom panel shows steps in recall if prior rehearsal has not occurred.

If recall based on either the rehearsal chain or original stimulus chain fails (e.g., because one or more relevant items have disappeared from auditory working memory), then the recall process cleans up and terminates, returning control to the overall task strategy. Our present EPIC model makes no attempt to guess the identities of missing items during recall or to produce them on the basis of residual information in auditory working memory. This restriction is justifiable for now because we focus exclusively on studies that scored performance as being correct if and only if the entire sequence of words presented on a trial was recalled in original order. Under such conditions, random and sophisticated guessing contribute negligibly little to obtained data.

Under other conditions, however, various types of supplementary guessing process may make substantial contributions, especially when credit is given for partially correct responses. Consequently, we have experimented with augmented EPIC models that incorporate such processes. These hold promise of accounting for patterns of data beyond those considered in this chapter (e.g., shapes of serial-position curves), but they are also much more complex, so we do not discuss them further here. Nevertheless, in the future, it will be important for both us and other theorists to develop these models more fully, because guessing strategies -- rather than architectural mechanisms (e.g., residual graded activation levels; cf. Anderson & Matessa, 1997; also see Engle et al., Lovett & Reder, this book) -- may be primarily responsible for many ancillary phenomena observed during the performance of typical verbal working-memory tasks.

Applications of EPIC Model

To test the present EPIC model, we have applied it in accounting for results from two representative studies with the serial memory-span task.

The first of these is a classic study by Baddeley et al. (1975, Exp. 1). Empirical data from it are especially interesting and challenging because they embody large interactive effects of sequence length (number of items per sequence) and articulatory duration (time to vocalize a presented sequence). This interaction, together with other supplementary results, has led some investigators (e.g., Schweickert & Boruff, 1986) to infer that items stored in auditory working memory endure for only about 2 s.

The second study whose results are modeled here has been conducted by Longoni et al. (1993, Exp. 1). Its empirical data are interesting because they embody interactive effects of phonological similarity and articulatory suppression. These effects led Longoni et al. to infer that "the form of storage responsible for the (phonological similarity) effects must be functionally independent from the (subvocal rehearsal) processes that are manifested in the effect of (sequence) length. Indeed, the capacity of phonological storage seems to be a constant number of words, regardless of the number of phonemes or syllables that they contain, which suggests that the functional units of phonological storage are ... discrete words rather than their constituent phonemes or syllables" (1993, pp. 13-14).

In what follows, we next discuss Longoni et al. and then Baddeley et al.

Longoni et al.'s Study

The generic version of the serial memory-span task described earlier was used in the study by Longoni et al. (1993, Exp. 1).

Experimental design. On each trial, four auditory Italian words were presented successively to participants for subsequent recall in original order. During presentation of the word sequence and subsequent attempted recall, the participants either rehearsed the words covertly, or they performed a secondary articulatory-suppression task, which presumably precluded covert rehearsal. Subsequent recall attempts were produced in writing so that when required, articulatory suppression could continue throughout the trial.

Under both the articulatory-suppression and rehearsal conditions, some word sequences contained two-syllable words, whereas other word sequences contained four-syllable words. As measured by Longoni et al., the mean times that participants took to vocally articulate the

sequences of four-syllable words were longer than those for the sequences of two-syllable words. Furthermore, the words in a sequence were either phonologically similar to or distinct from each other. Across trials, the phonological-similarity and articulation-time factors varied in a quasi-orthogonal manner. Four different pools of words were used to achieve this manipulation.

Overall, the experiment thus had a 2 (suppression/rehearsal) by 2 (short/long articulation time) by 2 (phonologically similar/distinct) factorial design. The inclusion of such multiple factors has important virtues. However, the absence of more than two levels within each factor also seriously limits the design's power.

Empirical results. The dark textured bars in the top and bottom panels of Figure 5 show the empirical results from Longoni et al.'s (1993, Exp. 1) study in terms of percent correct recall (i.e., percentages of trials on which participants recalled all words in correct order). All three independent variables had reliable main effects. Articulatory suppression, long articulation times, and phonological similarity each decreased percent correct recall substantially. Some reliable interactions also occurred. For example, the effect of articulation time was much less under the articulatory-suppression (rehearsal absent) condition than under the non-suppression (rehearsal present) condition. In contrast, phonological similarity tended to magnify the articulation-time effect.

EPIC computational model. In applying our EPIC computational model to account for these results, we decided that it was not necessary to simulate handwriting for final recall or to simulate articulatory suppression per se. Instead, we programmed the model's task strategy simply to suspend its rehearsal process (Figure 3) under the articulatory-suppression condition, and to recall words orally by using the stored traces of items from either internal (subvocal rehearsal) or external (overt auditory stimuli) sources in auditory working memory, depending on whether or not rehearsal had taken place. This treatment makes the plausible assumptions that articulatory suppression completely precluded participants' subvocal rehearsal, and that the model's vocal rate of recall approximately equalled participants' actual rate of written recall. Our simulation of performance by Longoni et al.'s participants therefore used their reported articulation rates as parameters.

To implement the simulation, we ran the model through Longoni et al.'s experimental procedure. In response, the model produced a sequence of correct and incorrect recall attempts. An iterative search was used to identify values of M and s, the parameters of the item decay-time distributions, that yielded maximally good fits between simulated and empirical results. Four pairs of M and s values were identified, including ones respectively associated with item codes for phonologically similar and distinct words from external (overt auditory stimuli) and internal (covert rehearsal) sources. In identifying these values, it was assumed that articulation time and articulatory suppression did not affect them.

Simulation results. The white bars in the top and bottom panels of Figure 5 show simulation results produced by the present EPIC model for Longoni et al. (1993, Exp. 1). We obtained an accurate quantitative account of the main effects and interactions caused by all three of Longoni et al.'s independent variables.

Table 1 shows our model's parameter values for the decay-time distributions as a function of the items' phonological similarity and source (external or internal). The mean decay times that yielded good fits to the empirical results were longer for phonologically distinct items and for items whose source was external. These two trends tended to be overadditive. In contrast, the spread parameters of the decay-time distributions were less for items whose source was external, and they did not depend on phonological similarity.

Theoretical interpretation. There is a straight-forward theoretical interpretation of these simulation results. Basically our EPIC model's assumptions may be correct! Elaborating the ideas of some previous theorists (e.g., Baddeley, 1986), the model provides a neat explanation of the articulatory-suppression effect. Performance is worse without rehearsal because only the original traces of external stimulus items are potentially available in auditory working memory to be recalled. However, following covert rehearsal, recall also may be based on traces of items generated internally through the model's phonological loop, because the rehearsal process generates fresh copies of them repeatedly.

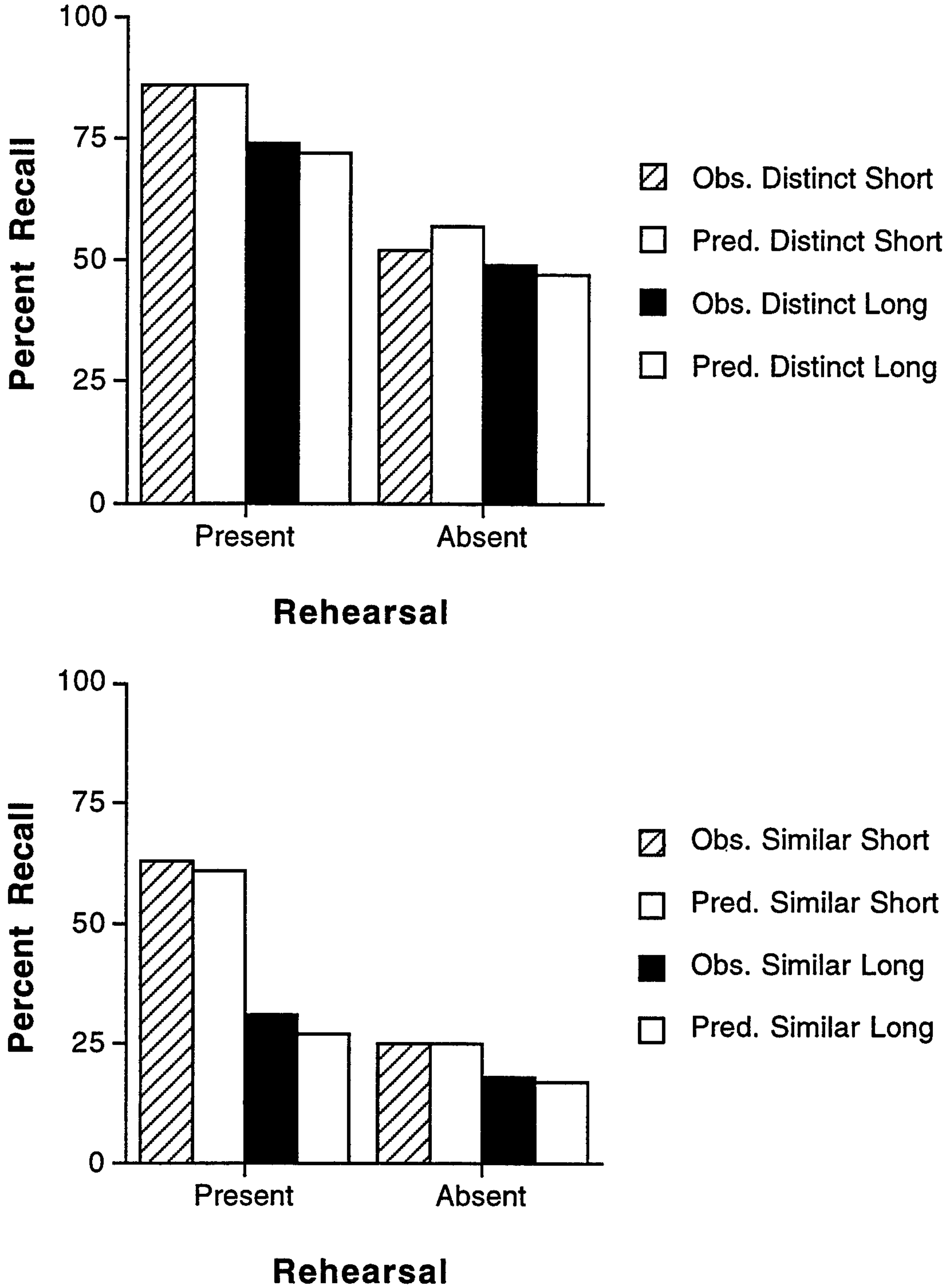


Figure 5. Empirical and simulation results for Longoni et al. (1993, Exp. 1). Dark textured bars represent observed percentages of trials on which serial recall was perfectly correct as a function of sequence articulation time and articulatory suppression (rehearsal absent) versus non-suppression (rehearsal present). White bars to right of dark bars represent corresponding predicted percentages of correct-recall trials under the present EPIC model. Top panel: Observed and predicted percent correct recall with sequences of phonologically distinct words. Bottom panel: Observed and predicted percent correct recall with sequences of phonologically similar words.

Table 1. Parameter Values in EPIC Simulation for Study by Longoni et al. (1993)

Source Type	Phonological Status	*M* (ms)	*s* (ms)
external	similar	6625	0.2
	distinct	7400	0.2
internal	similar	4875	0.5
	distinct	5500	0.5

Note: *M* is the median of the lognormal decay-time distribution for items in auditory working memory; *s* is the distribution's spread parameter. The left two columns of the table indicate the characteristics of the stored items for which these parameter values were identified. The external source corresponds to overt auditory stimulation, and the internal source corresponds to covert vocal rehearsal.

The model likewise explains the interactive articulation-time and phonological-similarity effects. Item sequences that take more time to articulate are recalled less well because the rehearsal and recall processes proceed more slowly through them, so items are more likely to be lost prematurely from auditory working memory. Phonologically similar items are recalled less well because their shorter decay times tend to preclude the rehearsal process from maintaining them. The articulation-time effect during rehearsal is greater for phonologically similar items because their shorter decay times make them disproportionately more likely to get lost during lengthy rehearsal cycles.

Concomitantly, the parameters of the decay-time distributions (Table 1) have an interesting interpretation. Given that different mean decay times were required for items that had external and internal sources, the present simulation suggests that source-specific coding does take place in human auditory working memory. This supports previous claims about multiple types of auditory working-memory codes (Cowan, 1984). Likewise supported is the claim (Posner & Konick, 1966) that phonologically similar items decay more quickly than do distinct items.[6]

Technical lessons. Our work here also offers some instructive technical lessons. Although the goodness-of-fit produced by the present simulation was satisfactory, the data reported by Longoni et al. did not contain enough degrees of freedom for a completely convincing test. Fitting the EPIC model involved adjusting six parameters (Table 1), including four values of *M* and two values of *s*, whereas the data came from a 2-by-2-by-2 factorial design with only 8 d.f. This deficiency highlights a serious limitation of binary factorial designs. Although common in

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[6] Intriguingly, Longoni et al. (1993, Exp. 1) found that sequences of phonologically similar words took longer to articulate than did sequences of distinct words. At first blush, this finding seemed potentially sufficient to explain why the sequences of similar words were recalled less well. However, a preliminary simulation with our EPIC model revealed that by itself, the articulation-time difference between similar-word sequences and distinct-word sequences could not account entirely for the worse recall of the similar-word sequences. Fitting the data well also required there to be a difference between the mean decay times of similar and distinct words. Such a discovery illustrates the superiority of precise computational modeling over informal verbal theorizing for determining what conceptual constructs are truly necessary.

cognitive psychology, such designs are an "underpowered" source of data, because they yield only nominal-scale information about the effects of their independent variables. Future experimentation instead should use designs that have several levels per factor.

Yet despite these caveats, it would be mistaken to dismiss the initial success of the present EPIC model as trivial. Our simulation for Longoni et al.'s study was constrained by the model's architecture and task strategy. So even with six free decay-time parameters, there was not arbitrarily great freedom to fit the data. That the model accounted for the overall pattern of reported factor effects thus should be taken as an encouraging sign about the model's theoretical value. Further confirmation of this comes in our work with Baddeley et al.'s (1975, Exp. 1) study.

Baddeley et al.'s Study

Fortunately, Baddeley et al.'s (1975, Exp. 1) classical study had an experimental design with ample power for a strong test of our EPIC model. This power stemmed from there being an independent variable that had several levels within it, namely, the number of words per sequence. After we adjusted the model's free parameters, numerous degrees of freedom remained in Baddeley et al.'s data to assess the model's goodness-of-fit carefully.

Experimental design. Baddeley et al.'s study used the generic serial memory-span task described before. On each trial, either 4, 5, 6, 7, or 8 auditory English words were presented successively to participants for subsequent recall in original order. The participants always were allowed to rehearse; no articulatory suppression was required. Subsequent recall attempts were oral. Within each sequence, the words took either relatively long or short times to articulate. Across trials, the number of words per sequence and the sequence's articulation time varied systematically. Overall, the experiment thus had a 5 (number of words per sequence) by 2 (short/long articulation time) factorial design. The sequences involving long articulation times were constructed from a pool of five-syllable words; a pool of one-syllable words was used to construct the sequences involving short articulation times.[7]

Empirical results. The dark textured bars in the top and bottom panels of Figure 6 show the empirical results from Baddeley et al.'s (1975, Exp. 1) study in terms of percent correct recall. Both independent variables had reliable main effects. As either the number of words per sequence or the sequence articulation time increased, percent correct recall decreased substantially. A reliable interaction also occurred between these effects. The number of words per sequence had a much greater effect for the sequences whose articulation times were long.

EPIC computational model. To account for these empirical results, we ran our EPIC model through Baddeley et al.'s experimental procedure. In response, the model produced a sequence of correct and incorrect recall attempts. A single pair of mean and spread parameter values, identified by iterative search, was used for the item decay-time distributions: $M =$ 7500 ms; $s = 0.2$.[8]

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[7] A confounding therefore existed here between number of syllables per word and articulation time. Nevertheless, more recent research by Baddeley and others, including us, has revealed that sequence articulation time per se is a crucial independent variable. This finding stands despite counter objections by a few investigators (cf. Caplan, Rochon, & Waters, 1992).

[8] Because no articulatory suppression occurred in Baddeley et al.'s (1975, Exp. 1) study, it was not possible to accurately estimate different means and spreads for the decay times of items from external and internal sources. In this case, we therefore adopted the default assumption that these parameters did not differ as a function of the items' source Also, we again assumed that sequence length and articulation rate did not affect them either. Thus, there were many fewer free parameters in our simulation for Baddeley et al. than in our simulation for Longoni et al.

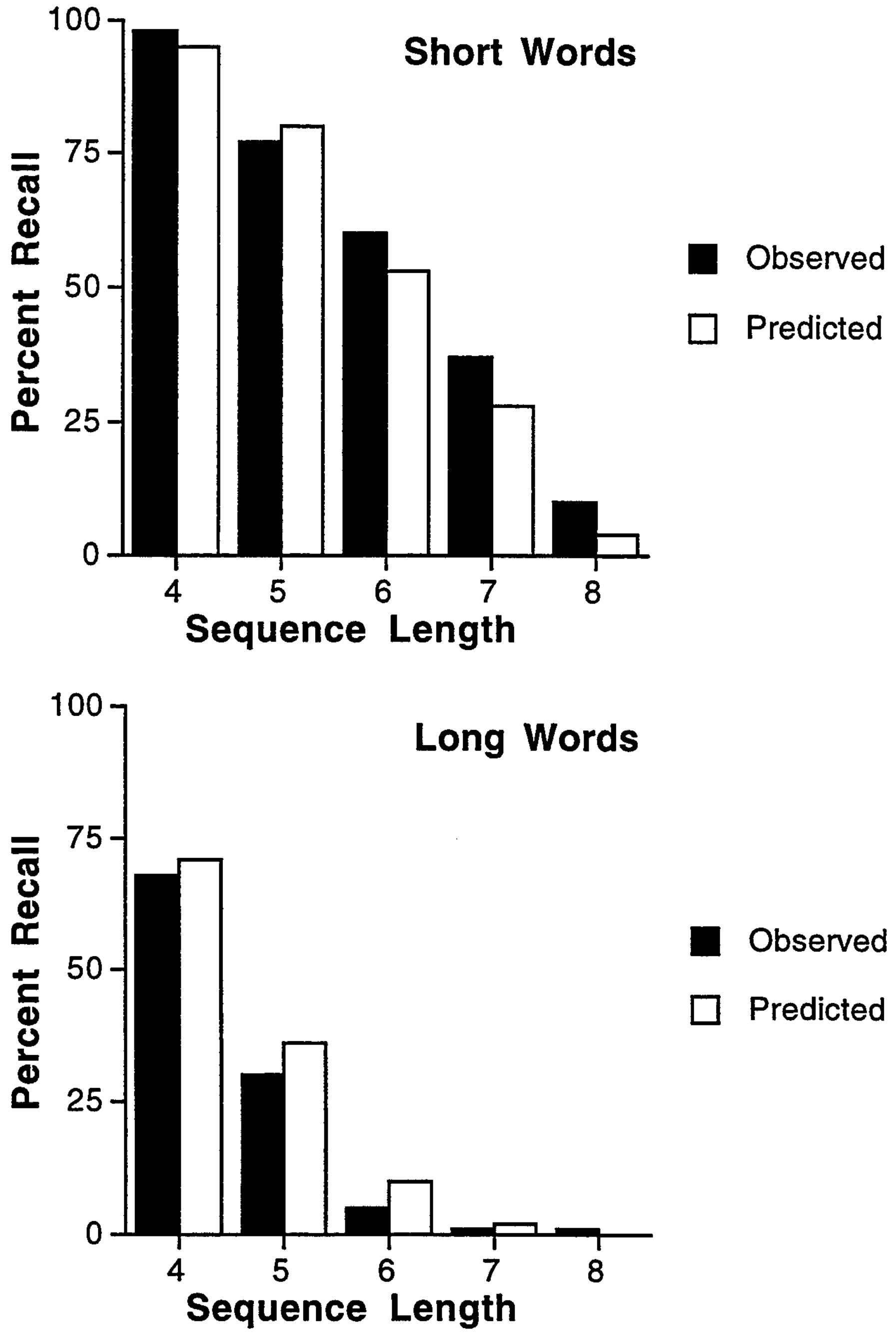

Figure 6. Empirical and simulation results for the study by Baddeley, Thompson, and Buchanan (1975, Exp. 1). Dark textured bars represent observed percentages of trials on which serial recall was perfectly correct as a function of sequence length (i.e., the number of words per sequence). White bars adjacent to the right of the dark bars represent corresponding predicted percentages of trials on which serial recall was perfectly correct under the present EPIC model of verbal working memory. Top panel: Observed and predicted percent correct recall with sequences that contained short (one syllable) words and had short articulation times. Bottom panel: Observed and predicted percent correct recall with sequences that contained long (five syllable) words and had long articulation times.

For the present simulation, we also needed to set the rates at which the words were vocalized in the sequences that had nominally "short" and "long" articulation times. Unfortunately, Baddeley et al. (1975, Exp. 1) did not report these rates. We therefore measured them ourselves by vocalizing representative word sequences at a crisp comfortable pace of the sort typically used during covert rehearsal. The mean rates of vocalization for the sequences of words with long and short articulation times were measured respectively to be 804 ms and 419 ms per word. These rates were then used in our EPIC model.

Simulation results. The white bars in the top and bottom panels of Figure 6 show the simulation results produced by our model for Baddeley et al. (1975, Exp. 1). We obtained an accurate quantitative account of the main and interactive effects caused by both the sequence-length and articulation-time factors. This success occurred even though the present simulation used many fewer free parameters than there were degrees of freedom in the empirical results.

Theoretical interpretation. Our EPIC model fit well here because it aptly characterizes the contributions of various item representations, subvocal rehearsal, and item decay in auditory working memory. To do so requires having precisely and veridically specified the task strategy through which the contents of auditory working memory are managed. It therefore appears that for the serial memory-span task, we have successfully encompassed several auditory working-memory mechanisms and arrived at a more complete description of the human phonological loop.

Substantive and Methodological Insights Concerning Verbal Working Memory

From our applications of EPIC to the data of Longoni et al. (1993, Exp. 1) and Baddeley et al. (1975, Exp. 1), several substantive and methodological insights concerning verbal working memory have been attained.

Duration of items in auditory working memory. In each simulation with the present EPIC model, the mean durations of auditory working-memory items were two to four times greater than the 2 s claimed from some prior studies that have used the serial memory-span task (e.g., Baddeley et al., 1975; Schweickert & Boruff, 1986). Instead, the item durations suggested by our modeling are more consistent with research on echoic and auditory memory that has used other types of paradigm, which point toward values around 10 s or greater (e.g., Balota & Duchek, 1986; Cowan, 1984; Cowan et al., 1990; Eriksen & Johnson, 1964; Watkins & Todres, 1980). What could account for this conflict? Perhaps previous theorists have neglected to consider how much executive control might lengthen the time consumed by covert rehearsal during sequence-presentation intervals when partial chains of memorized items are being constructed and elaborated by task-strategy procedures. If so, then they would not have realized that items in auditory working memory must endure for at least as long as such processes take, which -- as our modeling shows -- may be substantially longer than the time required to utter a sequence of items after it has been fully prepared. Attaining such realizations constitutes a strong incentive for seriously pursuing formal theoretical approaches.

Source-based coding. A second insight provided by the present work is that distinct codes are indeed used in auditory working memory for items that come from external (overt auditory stimulus) and internal (covert speech) sources. Specifically, we discovered that "imaginal" codes for internal-source items have shorter and more variable durations than do "literal" codes for external-source items (Table 1). This helps explain some of the complexity that has characterized the past literature on auditory memory (Cowan, 1984).

Importance of task strategies. Like our prior research in other task domains, the present research demonstrates the crucial importance of characterizing task strategies. For understanding working memory, this characterization is necessary even in seemingly simple cases like the serial memory-span task. The executive control needed to perform this task is not trivial, involving several temporally overlapped threads of processing. Had we also chosen to model the sophisticated guessing processes that contribute to partially-correct recall attempts, the importance of task strategies would have been even more apparent. Future theorizing and experimentation about working memory therefore needs to take task strategies much more seriously (cf. W. Reitman, 1970).

General Discussion

An important exercise for facilitating future research is to compare and contrast alternative theoretical frameworks being used currently to characterize human working memory. By doing so, commonalities among these frameworks may be identified, and theoretical integration may be fostered. Also, to the extent that there really are fundamental differences among frameworks, focusing on them may yield crucial empirical tests for determining which theories are most viable. Toward achieving these objectives, the editors of this book (Miyake & Shaw, in press) have posed the contributing authors with eight designated questions. We are now in a position to answer them on the basis of EPIC. Table 2 summarizes our answers to the eight designated questions.

Answers to Eight Designated Questions

Basic mechanisms and representations in working memory. Working memory in EPIC is mediated by a variety of specific mechanisms. The architecture's perceptual and motor processors encode information and put symbolic representations in modal working-memory stores, such as auditory and visual working memory. These representations are accessed, maintained, and used for task performance by the cognitive processor, which applies sets of production rules to interact with the modal working-memory stores and perceptual-motor processors. Applying its production rules, the cognitive processor also maintains and uses symbolic representations in the control and tag stores of working memory for directing the flow of processing.

For example, many of these mechanisms and representations contribute crucially to our EPIC model of performance in the serial memory-span task. Sets of production rules in the cognitive processor, together with the auditory perceptual processor, auditory working memory, and vocal motor processor, implement the model's phonological loop. Coordinating item-chain construction, rehearsal, and recall processes under the model also requires manipulating items in the control and tag stores of the architecture's production-system working memory.

Control and regulation of working memory. As our model further illustrates, EPIC has no separate general-purpose "central executive" per se (cf. Baddeley & Logie, this book). Instead, the cognitive processor is programmed with specific sets of production rules to implement executive control (e.g., an overall task strategy) for performing particular tasks. These rules have the same format as other rules used in various individual subtasks (e.g., covert rehearsal and overt recall). A principal function of the executive control processes in EPIC is to coordinate progress on various subtasks so that they get completed correctly and efficiently. This involves managing the contents of EPIC's working-memory control and tag stores with respect to task goals, step items, strategy items, status items, and tags, which govern when subtask processes are executed and what perceptual-motor resources are made available to them at each moment along the way.

Unitary versus non-unitary nature of working memory. Despite a deceptive impression that Figure 1 might create initially, by now it should be clear that working memory is not a single "construct", "place", or "box" in EPIC. Rather, EPIC's working memory has somewhat the same status as does the "Self" in Buddhism (Bukkyo Dendo Kyokai, 1985); under various guises, it is at once both "everywhere" and "nowhere". More precisely, we conceive working memory to consist of multiple separable subcomponents. Some of these subserve the temporary storage and on-line use of declarative knowledge, such as perceptual (visual, auditory, tactile), motoric (ocular, manual, vocal), and procedural control (task goal, strategy item, status item) information. Other subcomponents subserve the application of procedural (production rule) knowledge that implements executive and task processes. Interactions among the various subcomponents of working memory occur through the operations of EPIC's cognitive processor.

The diverse and distributed multi-component nature of working memory in EPIC is illustrated by our present model of performance for the serial memory-span task. This model uses the architecture's auditory working memory, control store, and tag store to maintain complementary types of declarative knowledge during stimulus presentation, covert rehearsal, and overt recall. Implementation of these processes through the model's phonological loop also requires the cognitive processor to interact with the vocal motor processor and auditory perceptual processor.

Table 2. Brief Summary of Answers to The Eight Designated Questions

(1) For EPIC, what are the basic mechanisms and representations in working memory?

Information is encoded symbolically and put in modal (e.g., auditory and visual) working-memory stores by EPIC's perceptual and motor processors. Production rules in the cognitive processor, together with the perceptual-motor processors, are used to maintain and apply this information for task performance. The cognitive processor also uses production rules to maintain and apply symbolic information in the control and tag stores of working memory, which help direct the flow of processing.

(2) In EPIC, how is working memory controlled and regulated?

EPIC has no general-purpose "central executive" separate from other architectural components. Rather, working memory is managed by task-specific executive control processes. With respect to the particular task(s) for which skilled performance is being modeled, executive control processes are specified in terms of production rules that update, maintain, and use the contents of working memory to complete the task(s) efficiently.

(3) In EPIC, is working memory unitary or non-unitary ?

Working memory in EPIC consists of multiple separable subcomponents. Some of these subserve the temporary storage and on-line use of symbolic declarative knowledge, such as perceptual (visual, auditory, tactile), motoric (ocular, manual, vocal), and procedural control (goals, task priorities, process status) information. Other subcomponents subserve the application of procedural (production rule) knowledge that implements executive and task processes. Interactions among these subcomponents occur through operations by EPIC's cognitive, perceptual, and motor processors.

(4) In EPIC, what is the nature of working-memory limitations?

The philosophy of modeling embodied in EPIC aspires to parsimonius and plausible assumptions about human information processing. Accordingly, the limits of EPIC's working-memory capacity come mainly from two especially justifiable sources: finite processing speed, and decay of symbolic codes in partitions of perceptual working memory. No limits have been set yet on the capacities of EPIC's stores for production rules and procedural control information. Furthermore, EPIC has no limited supply of a general resource such as activation capacity.

continued on next page

Table 2. Brief Summary of Answers to The Eight Designated Questions, cont.

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(5) With EPIC, what is the role of working memory in complex cognitive activities?

EPIC's working-memory components play multiple supporting roles in task performance. For processing of verbal information, contributions are made by auditory working memory, vocal-motor working memory, and a procedural control store. Similarly, visual working memory, ocular-motor working memory, and the procedural control store contribute to processing of visuo-spatial information. Functional task analyses based on EPIC reveal that even the simplest tasks require working memory and executive control to be performed successfully.

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(6) In EPIC, what is the relationship of working memory to long-term memory and knowledge?

In EPIC, the partitions of working memory are structurally separate from LTM, but complement and interact with it. The production-rule store in EPIC's cognitive processor may be construed as a form of LTM for procedural knowledge. Given our objectives to date, EPIC's LTM for declarative knowledge has not been applied extensively yet to model skilled task performance. Nevertheless, it has the potential to represent and support the use of relevant symbolic knowledge structures as need be.

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(7) In EPIC, what is the relationship of working memory to attention and consciousness?

In EPIC, "working memory" and "attention" refer to different theoretical constructs. Through judicious executive control and orienting of physical sensors, priority may be given to processing some external stimuli rather than others (i.e., "attention to perception"). Also, priority may be given to producing some motor outputs rather than others (i.e., "attention to action"). This control is achieved by manipulating items in working memory (e.g., task goals) that determine which production rules are fired. The phenomenological experience to which "consciousness" refers ordinarily plays no role in EPIC.

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(8) How is EPIC related to the biological implementation of working memory?

The theoretical assumptions embodied in EPIC are consistent with current findings from neuroscience about working memory. For example, EPIC emulates extensively distributed parallelism of information processing and short-term storage through modular interactive mechanisms, as found in the human brain. Like those of the brain, EPIC's perceptual and motor mechanisms are treated as crucial subcomponents separate from and complementary to other cognitive mechanisms.

Nature of working-memory limitations. EPIC is predicated on a philosophy of theory construction and performance modeling that aspires to make plausible parsimonius assumptions. Limits on EPIC's working-memory capacity therefore come mainly from two especially justifiable sources: finite processing speed, and decay of symbolic representations in the modal (perceptual) working-memory stores. We have set no limits yet on the capacities of EPIC's stores for production rules and procedural control information. Furthermore, EPIC has no limited supply of a general resource like activation capacity. In these respects, our theoretical framework differs significantly from those of some other contributors to this book (cf. Cowan; Engle et al.; Lovett et al.).

The parsimony and plausibility to which we aspire in EPIC are exemplified by our present model for performance of the serial memory-span task. According to it, percent correct recall depends simply on the rates of item decay in auditory working memory and on the rates at which chains of stored items can be constructed, rehearsed, and recalled during each trial. From prior research (e.g., Brown, 1958; J. Reitman, 1974; Sternberg et al., 1978), we know that both of these basic limits probably exist. To the extent that the former (decay) rates are high and the latter (processing) rates are low, final recall will be poor. However, the rate of decay is not assumed to depend on the numerosity of the items in auditory working memory, nor are the processing rates -- which stem from the cognitive processor's cycle time -- assumed to depend on the numerosity of the production rules being used for task performance.

Role of working memory in complex cognitive activities. Given our ultimate research objectives, we have constructed EPIC to be especially suited for modeling complex cognitive activities associated with skilled perceptual-motor performance in task situations such as aircraft-cockpit operation, air-traffic control, and speed-stressed human-computer interaction (Kieras & Meyer, 1997; Meyer & Kieras, 1998). In EPIC, some working-memory components (e.g., control store and tag store) contribute especially to the executive control of task scheduling and to the allocation of perceptual-motor resources among various subtasks, which play crucial roles during realistic multiple-task performance. Complementing these contributions, other components -- including EPIC's modal working-memory stores -- retain coded sensory and motor information that is needed for on-going interactions with the physical environment.

Indeed, functional analyses based on EPIC reveal that to be performed successfully, even the simplest tasks require working memory and executive control (Meyer & Kieras, 1997a, 1997b). As our present model of performance in the serial memory-span task illustrates, auditory working memory, vocal-motor working memory, the control store, and the tag store are all essential for processing elementary verbal information. Similarly, visual working memory, ocular-motor working memory, the control store, and the tag store are all essential for processing elementary visuo-spatial information. Presumably these mechanisms would be involved in more complex cognitive activities as well and may help constitute future models that we formulate to characterize realistic multiple-task performance.

Relationship of working memory to long-term memory and knowledge. EPIC's working memory is not simply an activated portion of long-term memory (cf. Cowan, Engle et al., Lovett et al., this book). Instead, various working-memory partitions and temporary stores in our architecture are structurally separate from long-term memory. Nevertheless, their contents and those of long-term memory can interact through operations mediated by the cognitive processor.

EPIC's working memory provides a substrate for procedural skills to exploit available declarative knowledge during on-line task performance. The production-rule store in the cognitive processor may be construed as a form of long-term memory for procedural knowledge. Given our prevailing objectives, long-term memory for declarative knowledge has not been applied extensively yet in our modeling endeavors. This is evident, for example, from the present EPIC model of performance in the serial memory-span task, where the organization and activation of declarative long-term memory play no explicit role. However, declarative long-term memory in EPIC has the potential to represent permanent symbolic knowledge structures and to support their use as need be. We envision that learning and practice may influence working-memory limitations

and functions beneficially by enhancing both the efficiency of procedural (production rule) knowledge and the efficacy of organized declarative (propositional) knowledge (cf. Ericsson & Kintsch, Lovett et al., O'Reilley et al., Schneider, Young & Lewis, this book).

Relationship of working memory to attention and consciousness. How working memory relates to attention and consciousness is a complex and thorny issue with which cognitive psychologists have struggled at least since the time of William James (1890). The resolution of this issue hinges on the conceptual perspective that one has, and on the technical definitions that one adopts.

In EPIC, "working memory" and "attention" refer to different theoretical constructs. Through judicious executive control and orienting of physical sensors, EPIC computational models give priority to processing some external stimuli rather than others (i.e., "attention to perception"). Also, priority is given to producing some motor outputs rather than others (i.e., "attention to action"). This prioritization is achieved by manipulating items in the working-memory control store (e.g., task goals) that determine which production rules are fired. As a result, for example, eye movements to particularly interesting or important visual stimuli may be executed, and movements by one hand may be selected, prepared, and executed in preference to movements by the other hand. The new items that these activities cause to arrive in the modal working-memory stores are the products of attention, but they are not attention itself. Furthermore, in other respects, working memory and covert attention are even more distinct under EPIC, because for reasons of theoretical parsimony, we have not yet incorporated covert attention shifting as part of the architecture's perceptual processors (cf. Schneider, this book).

Consistent with the latter conservatism, the phenomenological experience to which "consciousness" refers ordinarily plays no role in EPIC. Unlike some daring philosophers of mind (e.g., Chalmers, 1996), we refrain from speculating here about how the architecture might yield this experience as an emergent property. No claims are made for now about whether our EPIC computational model of performance in the serial memory-span task is conscious during the execution of its procedures!

Biological implementation of working memory. Although EPIC is an architecture for symbolic computational modeling of task performance, its assumptions are nonetheless compatible with implementation at biological and neural levels. This compatibility should not be surprising. As Newell (1990) argued forcefully, principled symbolic computational modeling can be complementary -- not antithetical -- to biological and neural implementation. In fact, properties of human information processing at the neural level impose fundamental constraints that prospective architectures and symbolic computational models must take seriously and accommodate among their basic assumptions. By doing so, they enhance their empirical credibility and ultimate prospects for being implemented biologically. Conversely, biological and neural modeling may benefit from insights gained through symbolic computational modeling about the inherent functional characteristics of human information processing (e.g., see O'Reilly et al., and Schneider, this book).

Among EPIC's assumptions that are relevant in these respects, we have made several concerning the distributed, quasi-modularized, semi-autonomous, parallel nature of information processing. EPIC's perceptual, cognitive, and motor processors are assumed to operate simultaneously and asynchronously, just like parallel distributed processing in the brain does. The cyclicity of the cognitive processor's operations likewise mimic some of the brain's neural rhythms (Kristofferson, 1967; Ray, 1990). Various working-memory stores in EPIC may have corresponding manifestations in the brain. For example, it is possible that the control and tag stores of working memory are implemented by anterior parts (frontal lobes) of the brain, whereas the modal working-memory stores for visual, auditory, and other sensory information are implemented by posterior parts (e.g., temporal and parietal lobes). Some other contributors to this book hold similar views (e.g., O'Reilly et al.; Schneider).

These views are supported by recent evidence from brain-imaging experiments conducted on participants during their performance of representative working-memory tasks (e.g., Awh et al., 1996; D'Esposito et al., 1995; Jonides et al., 1993; Paulesu et al., 1993). This evidence reveals that during such performance, multiple interconnected regions in the anterior and posterior parts of

the brain are active, forming an apparent network of modules that subserve complementary functions, as we suggested above might be the case. The activation of these regions increases and decreases systematically, depending on exactly which functions are engaged by the prevailing task(s). Perhaps by collecting more such evidence in the context of new studies designed to test further hypotheses based on EPIC and other alternative information-processing architectures, progress can occur toward integrating theoretical frameworks like ours with the biological and neural domains.

Theoretical Caveats

Of course, more questions remain to be answered beyond the preceding designated eight. As presently formulated, our EPIC model does not directly accommodate all of the prominent factor effects that have been found during studies with the serial memory-span task. For example, Brown and Hulme (1995) have shown that performance of this task depends systematically on lexical and semantic properties of the items from which to-be-recalled sequences are constructed. Related findings like this have been reported by other investigators as well (e.g., Caplan, Rochon, & Waters, 1992; Gregg, Freedman, & Smith, 1989; Naveh-Benjamin & Ayres, 1986). Because of confoundings between sequence articulation times and other factors (e.g., see Wright, 1979), it is conceivable that our model can account for at least some of these results without resort to additional mechanisms. Nevertheless, a full accurate account of them still may require augmenting the model with further contributions from declarative long-term memory.

Dealing with other results, such as ones concerning the putative separability of item and serial-order information (e.g., Estes, 1972; Healy, 1974; Shiffrin & Cook, 1978), also may require modifications or elaborations in terms of sophisticated guessing strategies and memory representations based on hierarchical structures.[9] Which modifications and elaborations are most appropriate presumably can be determined best through precise computational modeling rather than just informal verbal theorizing. Computational modeling helps resolve theoretical controversies!

Directions for Future Research

Furthermore, our future research with EPIC will focus especially on the role of working memory in realistic high-performance tasks. By doing so, we may gain additional insights about how working memory really works during "cognition in the wild". Also, insights may be gained about how to facilitate practical speed-stressed performance through new interface designs and modified task requirements.

For example, consider whether the usability of human-computer interfaces can be enhanced by augmenting them with capabilities for recognizing and responding to an operator's spoken commands. Concerning this issue, many computer technologists have become convinced that such augmentations would provide fantastic enhancements. However, there is some troublesome evidence that operating an interface by spoken commands actually interferes with the performance of verbally-intensive tasks like text editing (Shneiderman, 1992). Such interference may occur too when task performance requires perceiving and classifying speech or other sounds as well as producing spoken commands. Could these disruptions stem from limitations of a phonological-loop mechanism on which operators rely during human-computer interaction? Perhaps we can answer this question more definitively by constructing future models of human-computer interaction that incorporate a phonological loop like the one in our present EPIC model of performance for the serial memory-span task. From this endeavor, it then may be possible predict

[9] Because of the representation of serial order that our present model uses for items in auditory working memory, losing an item of a sequence entails losing some information about serial order. Clever guessing strategies could compensate for some of this loss. Also, consistent with results of some investigators (e.g., Healy, 1974), separate representations of item and order information are feasible in EPIC. However, for the sake of parsimony, we have not implemented them yet.

more precisely when and how much particular interfaces that entail speech I/O will help or hinder task performance.

As another important example, consider tasks that require high performance in environments such as fighter aircraft cockpits, where overall situation awareness is crucial (Graves, 1997). Under these circumstances, if a fighter pilot loses situation awareness, the consequences can be fatal. Such losses may stem from excessive mental workload associated with the complex decisions, multiple-task coordination, and human-computer interaction that cockpit operations require. Thus, it is essential to understand how situation awareness can be fostered.

Yet the available theory regarding this matter has been distressingly vague (e.g., see O'Donnell & Eggemeier, 1986). We therefore hope that through future EPIC modeling of the perceptual, cognitive, and motor requirements in complicated cockpit operations, it will be possible to better characterize important aspects of situation awareness and mental workload, which could yield improved concepts and tools for designing cockpit systems. Of course, a key part of our anticipated endeavors will be to further clarify and computationally represent the mechanisms of working memory.

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